Energy Policy 130 (2019) 7–21

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Investigating, forecasting and proposing emission mitigation pathways for CO_2 emissions from fossil fuel combustion only: A case study of selected countries

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ARTICLE INFO

Keywords:
CO_2 emissions
Long short-term memory (LSTM)
Climate change
Forecasting
Forecast evaluation

ABSTRACT

In this study, we investigate the direction of causal relationship between carbon dioxide (CO_2) emissions from fossil fuel combustion only (CO_2EFFCO) and economic growth for the USA, China, Canada, and Nigeria by using annual time series data for the period 1990–2016. The results depict a unidirectional causality running from gross domestic product per capita to CO_2EFFCO for the USA, China, and Canada. However, no causality direction was found for Nigeria. Furthermore, with the quest to achieve cleaner energy targets, we formulate long short-term memory (LSTM) algorithm devoid of exogenous variables and assumptions required to forecast CO_2EFFCO for the USA, China, Canada, and Nigeria. Based on the performance of our algorithm, we propose emission-mitigation pathways for the countries herein to follow to achieve zero CO_2EFFCO by the year 2030. The emission-mitigation pathways demonstrate that intensifying and promoting current and future policies that mitigate CO_2EFFCO based on our projections are enough to reduce energy-related CO_2EFFCO to a considerable level.

1. Introduction

Controlling carbon dioxide (CO_2) emissions (Perera, 2018) requires setting emission mitigation targets (Dong et al., 2018). However, setting emissions mitigation targets are becoming complex (Bismark Ameyaw and Yao, 2018a,b) because both the energy demand necessary for economic development and the emission mitigation targets should all be considered. To reach a set emission mitigation target, frequent monitoring, evaluation, and adjusting energy policies are required (U.S. Energy Information Administration, 2017). Such monitoring, evaluation, and adjustments need a fast and reasonable estimation of CO_2 emission mitigation pathways. However, due to the pivotal role of energy in routine activities of all economic units (Suganthi and Samuel, 2012), Are policy regulations in adhering to the mitigating emissions from CO_2 sustainable and achievable? Also, does energy produced and consumed from conventional and exhaustible resources add-in to economic growth? Against this backdrop, countries like the United States of America (USA), China, Canada, and Nigeria have either taken necessary steps to reduce to a considerable level GHG emissions or has refused to adhere to emissions mitigation targets.

Based on the differences in economic structure, development level, and growth aims, it is somehow considerable for countries to be adamant about mitigating greenhouse gas (GHG) emissions. As a result, different countries are setting different GHG emission mitigation targets. For example, recent reports indicate that the USA has withdrawn from the Paris Agreement (Rutherford, 2017). Furthermore, the USA has also canceled the Green Climate Fund that was set up under the Paris Agreement to assist developing and emerging countries develop low emission energy technologies. China, being a core member of the Paris Agreement has firmly pledged to the Paris Agreement. China's top governmental bodies have approved the carbon trading system which aims to check the country's heavily polluting power plants (Parry et al., 2016). Under this trading system, power plants are issued with allowances to emit a certain amount of CO_2. Plants that manage to undershoot their targets by cleaning up and becoming more efficient will be able to sell their excess permits to other generators. Canada's Pan-Canadian Framework on Clean Growth and Climate announced in 2016 contains proposals for economy-wide measures, including a carbon

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https://doi.org/10.1016/j.enpol.2019.03.056
Received 9 January 2019; Received in revised form 26 March 2019; Accepted 27 March 2019
Available online 02 April 2019
0301-4215/

pricing plan and a plan to phase-out traditional coal plants (Government of Canada, 2017). The regulation plans to phase out coal-fired power plants by 2030, reduce methane emissions from the oil and gas sector, phase down the use of hydrofluorocarbons (HFCs), and introduce a clean fuel standard. The government of Nigeria Intended Nationally Determined Contributions (INDCs) noted that to meet its conditional and unconditional targets, the country has to end gas flaring by 2030, reduce dependency on fossil fuel powered generators, as well as to provide technical support to improve energy efficiency. The estimated national cost needed to meet the INDCs was projected to be more than US$100 billion (ICF International, 2016). It is asserted that Nigeria could not sign the Paris Agreement because the Agreement was deemed to be retrogressive and it would have undermined the country's development efforts.

Due to the difference in country-case opinions on meeting cleaner energy targets, researchers have taken up the mantle to investigate the seemingly plausible relationship between GHG emissions, energy consumption and economic growth with the aim of proposing policy implications or recommendations for Governments to adopt. Readers are becoming increasingly frustrated because conclusions made by researches have been inconclusive. Numerous research has employed two main techniques for analyzing the relationship between these three indicators. The first stream depicts an inverted U-shaped relationship between environmental pollutants and economic growth popularly known as the Environment Kuznets Curve (EKC) (Cho et al., 2014; Giovanis, 2013). Conclusions from these studies are varying due to country-level specificities (B. Ameyaw and Yao, 2018a, 2018b). The second stream examines the nexus between energy consumption and economic growth (Komal and Abbas, 2015; Tang et al., 2016). Likewise, conclusions drawn is inconclusive due to the choice of datasets, model specifications, and the econometric techniques involved.

Concerning the nexus between economic growth, energy consumption, and CO_2 emissions, there are three main discerning views in literature. The first considers that economic growth causes CO_2 emissions and vice versa, the second asserts that there is a causal nexus in both directions whereas the third, in contrast to the two aforementioned, argues that there is no causality running among the variables. For example, in the USA (Hsiang et al., 2017), found unidirectional causality running from pollutant emissions to economic growth, from energy consumption to economic growth, and from energy consumption to CO_2 emissions, all without feedback. Furthermore (Bildirici, 2017), concluded that there existed the bi-directional link among economic growth, biofuel consumption, biofuel consumption, economic growth, CO_2 emissions, and militarization. In China (Li et al., 2017), revealed that there exist unidirectional causalities running from GDP and oil consumption to CO_2 emissions, from GDP to oil consumption, and from coal consumption to oil and gas consumption. Also (Govindaraju and Foon, 2013), found strong evidence of unidirectional causality running from economic growth to CO_2 emissions. Also (Boamah et al., 2017), concluded that there exist the presence of long-run relationships amongst carbon dioxide emission, economic growth, energy consumption, imports, exports, and urbanization. For Canada (Hamit-haggar, 2012), found a unidirectional Granger causality running from economic growth to CO_2 emissions. As the enormous amount of emissions emitted into the environment in Africa is from Nigeria due to its oil production (B. Ameyaw and Yao, 2018a,b), researchers have taken an interest in analyzing the relationship between CO_2 emissions and economic growth. For instance (Jaiyeola, 2016), revealed that oil production and carbon emission had a significant adverse effect on real per capita growth. Also (Akpan and Akpan, 2012), concluded that in the long-run, economic growth is associated with increasing CO_2 emissions, while an increase in electricity consumption leads to a rise in CO_2 emissions. Furthermore (Alege et al., 2016), found the existence of unidirectional causation running from fossil fuel to CO_2 emissions and gross domestic product (GDP) per capita.

Although, varying conclusions have been drawn from the three main discerning views, understanding the nexus between CO_2 emissions, energy consumption, and economic growth is likely to help formulate energy policies as well as developing energy resources in sustainable ways. Therefore, this current study aims to analyze the long and short-run causal relationship between carbon dioxide emissions from fossil fuel combustion only (CO_2EFFCO) and economic growth for the USA, China, Canada, and Nigeria. The USA and China are the two topmost energy consuming countries in the world with high amounts of emissions (Steeves and Ouriques, 2016), Nigeria is also one of Africa's largest producer of oil with high levels of emissions (B. Ameyaw and Yao, 2018a,b), and Canada is declared to miss its Paris Agreement target to reduce economy-wide GHG emissions to 30 percent below 2005 levels by 2030 ("Canada's Climate Action Tracker," 2017). Such a relational analysis is lacking in literature as much emphasis is placed on CO_2 emissions and economic growth. Furthermore, this study goes on to formulate its own Long Short-Term Memory (LSTM) algorithm which entirely hinges on univariate forecasting with zero causal variables and assumptions required for prediction. As it univariate forecasting has existed for decades (Bismark Ameyaw and Yao, 2018a,b) with literature such as (Hu and Jiang, 2017; Abdel-Aal, 2008; Ma et al., 2018) employing univariate forecasting technique, our algorithm formulation which leverages recurrent neural network (RNN) LSTM sought to develop and apply a single-high-accuracy CO_2EFFCO forecasting technique devoid of deterministic variables, assumptions, and scenarios and with the capability of predicting CO_2EFFCO for long-term. We leverage the power of artificial neural networks (ANNs) in developing such high-accuracy own-data-driven forecasting technique. Using authors' LSTM algorithm formulation in predicting future CO_2EFFCO for USA, China, Canada and Nigeria in a single manuscript is lacking in literature as of now. Also, as policymakers rely on projections made by researchers in drafting comprehensive policies necessary to achieve set targets, recent studies from (Van Den Bergh, 2017; Korsbakken et al., 2016; Hulme, 2016; Peters et al., 2017; Keohane and Victor, 2016) have highlighted that the current Internationally National Determined Contributions (INDCs) are insufficient in achieving the energy-induced share of the 1.5 °C global warming target. By so doing, we end by forecasting CO_2EFFCO to the year 2030 and propose emissions-mitigations pathways for the countries employed herein to help these countries make decisional analysis and intensify their investments on the seemingly impossible achievement of zero emissions. Such CO_2EFFCO emissions-mitigation pathways are also lacking in literature.

2. Country-case CO_2EFFCO and its recent mitigation policies

The combustion of fossil fuels has an adverse health effect on human and ecological safety (B. Ameyaw and Yao, 2018a,b). For instance, the burning of fossil fuel for electricity generation, heating, transportation, and industrial purpose emits dangerous toxins into the environment which threatens the life of all species on earth (Perera, 2018). Due to this, many economies have introduced measures to spur an effort to mitigate CO_2EFFCO. This section explains policy reviews enacted by the countries employed herein for reducing GHG emissions. We concentrate on GHG emissions because CO_2EFFCO forms a core component of GHG emissions. Any policy instrument adopted or enacted to mitigate GHG emissions has a significant positive effect in mitigating CO_2EFFCO in the long-run.

2.1. USA policies for mitigating CO_2 emissions

GHG emissions in the USA are generated from many discrete sources such as generation from power plants, households, commercial buildings, vehicles, industrial facilities and agricultural activities (Ramseur, 2017). As of 2015, it was concluded that CO_2EFFCO (petroleum, coal, and natural gas) accounted for approximately 76% of total USA GHG emissions (Ramseur, 2017). Such a conclusion shows that successful efforts to mitigate CO_2EFFCO would have a significant impact on

mitigating total CO_2 emissions to achieve greener-energy targets. With greener-energy targets looming, the USA holds a great deal of potential not just for reducing CO_2EFFCO but for mitigating GHG emissions in general. For federal climate policies, the USA federal government has implemented numerous executive orders in targeting climate change mitigation and adaptation. Some of the many initiatives implemented by the federal government for the last decade include vehicle emission standards, renewable energy tax credits, the CPP, and several attempts at passing legislation for the implementation of nation-wide cap and trade system (Redfern, 2013). Aside from climate change policies from the federal government, there are also numerous state-level policies aimed at reducing local GHG emissions. The most common state-level climate policy is the Renewable Portfolio Standard (RPS) whereby States under this initiative set a specific percentage for the consumption of renewable energies from renewable energy sources like wind, biomass, geothermal, biomass and distributed photovoltaic power. Also, one of the dominant market-based regulatory initiative among the states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont to cap and reduce CO_2 emissions from the power sector is the Regional Greenhouse Gas Initiative (RGGI). With the RGGI initiative, fossil fuel power plants are required to produce the excess of 25 MW to ascertain the allowance for each ton of CO_2 emitted every year. The emission allowance gathered by the participating States can be sold. Proceeds from the sales under this initiative should be invested in energy efficiency and renewable energy generating sources.

Under the USA new federal regime, USA's contribution to global climate change is slick due to its rollback on the CPP. It is asserted that the reversal on the climate action plan would create an additional 1.8 gigatonnes of CO_2 in 2030 which is approximately 31 percent excess of 2005 USA emissions (Akimoto et al., 2018). Recently, the USA's Environmental Protection Agency (EPA) has proposed the affordable Clean Energy (ACE) Rule which would replace the CPP. The ACE aims to encourage States to reduce GHG emissions by providing modern and affordable energy. Also, the ACE is expected to lay-out emission guidelines for States to brainstorm future strategies in addressing GHG emissions, especially from coal-fired power plants.

As the future is uncertain, there is no evidence as to whether or not the policy in the ACE will mitigate GHG emissions. Therefore, to reduce CO_2 emissions, the USA being the second largest emitter of GHG globally (Mohajan, 2014) is a viable case study to employ in this study.

2.2. China's policies for mitigating CO_2 emissions

Recently, China has outlined its 13th Five Year Plan (FYP) for mitigating emissions from CO_2. Under this FYP (2016–2020) initiative, China has committed to a reduction in carbon intensity of 40 percent to 45 percent by 2020 from 2005 levels (Zhang, 2015). Also, under this policy initiative, China plans to increase its primary energy consumption from non-fossil fuel to approximately 15 percent by 2020. This policy initiative has intensified efforts to efficiently consume energy by reducing carbon emissions in the most energy-intensive sectors. On the regional level, the total energy consumption by China's major cities is projected to be more than 60 percent (Dong et al., 2018). Such a projection means that cities play a far more significant role in shaping CO_2 emissions. Against this backdrop, China has launched the Low-Carbon City Pilots (LCCPs) initiative in thirty-six (36) essential cities under six (6) provinces (den Elzen et al., 2016). This LLCPs has compelled cities to set stringent carbon intensity targets to meet CO_2 emissions peaks in 2030. Cities under this LLCPs initiative are admonished to engage in promoting the generation of renewables and enhancing carbon sequestration. Furthermore, to genuinely transform into a low-carbon economy, China has step-up its carbon emission trading policy initiative (ETS) (Liu et al., 2017). The ETS creates a carbon market where emitters can buy and sell emission credits. This initiative does not just limit emissions but gives freedom to polluters to either reduce or purchase emission allowances from other issuers. This scheme aims to help China achieve its INDCs (M. Zhang et al., 2017a).

China has gradually moved to a center stage under the Paris Agreement in achieving the global target to limit temperature rise to two degrees Celsius by 2100. China has pledged its efforts to make such a target and has encouraged other parties under this agreement to follow suit. The overall picture for emission mitigation is not an easy tool as the pronouncements of policies may suggest. For instance, the feasibility and costs, as well as the rationale behind such policy pronouncements, may be unclear. Also, as the future remains uncertain, policy initiatives can just be intensified now, but there is no guarantee that it can be realized. With China being the world's largest emitter of CO_2, it is vital to employ China as a case study to investigate its emissions mitigation pathways.

2.3. Canada's policies for mitigating CO_2 emissions

Canada currently faces a gap of approximately 200 megatonnes to reach its GHG mitigation targets for the year 2030 ("The Emissions Gap Report," 2017). To bridge this gap, Canada is working in coordination with its provinces and territories to adopt national emission mitigation policies. Detailing Canada's strategies for CO_2 emissions mitigation, Canada's carbon pricing system is expected to reduce emissions by driving clean environmental innovative systems (Parry and Mylonas, 2018). This initiative will hinge on two main components: charges will be applied on the supply of fossil fuels; and there will be separate pricing for industrial facilities that are deemed emissions-intensive and trade exposed, known as the output-based pricing system (OBPS). Canada's OBPS policy initiative gives price incentives to companies for reducing their GHG emissions drastically. Under the OBPS, charges will not be paid on the purchase of fossil fuels. Instead, the carbon price will be charged on emissions above the threshold limit which is to be determined based on relevant output-based standards. Industrial facilities that emit less than the specified threshold will receive surplus credits for the aggregated portion of their emissions below the threshold limit. Facilities will be permitted to trade their surplus credits as a way of creating an incentive scheme for Canada's industrial sector to reduce carbon emissions below the threshold limit.

However, Canada's recent policy initiative on the carbon pricing system and the OBPS may have some administrative challenges. For example, collecting taxes after distilling crude oil may have some more significant advantages over taxes collected at the point of extraction because carbon emission cost tends to be more accurate when fuels are already processed (Parry and Mylonas, 2018). Imposing downstream carbon pricing at the point of combustion might be less comprehensive because such a pricing scheme only captures emissions above an annual threshold but fails to achieve the upstream pricing of fuels in buildings and vehicles. In general, an element of downstream pricing is a useful tool to combat emissions, but that should cover process emissions. With this likely administrative challenges, it is unclear as to whether Canada can meet its mitigation target by 30 percent from 2005 levels by 2030. Therefore, Canada's gap required to reach its policy agreement makes Canada a good case study to employ.

2.4. Nigeria's policies for mitigating CO_2 emissions

Nigeria is endowed with substantial oil accumulations estimated to be in abundance for the next forty-one (41) years at 2011 production levels (Otene et al., 2016). However, the sustainability of Nigeria's rich oil reserve is very dicey due to the adverse effect emissions has on the environment and human population. Given Nigeria's status as a fossil fuel dependent economy (Akinwande, 2014), Governmental of Nigeria

is taking skeptical policy initiatives towards a green economy. Although Nigeria is a signatory to the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol, the country has no binding agreement and obligation to reduce its GHG emissions under these two conventions. As a developing country, Nigeria is eligible to obtain financial assistance and technology transfer for GHG mitigation and adaptation purposes. Currently, international bodies such as the United Nations Development Programme (UNDP), the World Bank and the Global Environment Facility (GEF) have been investing in low-carbon projects in Nigeria. Recently, Nigeria's Renewable Energy Master Plan (REMP) which aims to increase the contribution of renewable energy was sponsored by the UNDP. The REMP policy primarily hinges on increased electricity supply and consumption from renewables, improved grid reliability, and security. The World Bank partnered with Nigeria's Federal Ministry of Environment to raise a $100 million Clean Technology Fund (CTF) for the deployment of alternative renewable energy sources for Nigeria. The World Bank's investment in Nigeria's CTF helps in the implementation and transfer of low-carbon technologies as well as scaling-up financial opportunities for investments into low-carbon energy sources. Furthermore, Nigeria, Africa's largest exporter of crude oil, has approved a national climate change policy initiative enacted to mitigate GHG emissions (Eleri et al., 2013). The Nigerian Federal Executive Council (FEC) has recently passed a policy initiative known as the National Policy on Climate Change and Response Strategy (NPC-RS) to tackle carbon emissions and other climate change environmental issues.

Irrespective of the recent policies and financial opportunities available for Nigeria to reduce carbon emissions and GHG emissions in general, there may be future concerns as to whether or not Nigeria can reduce its carbon emissions due to its over-reliance on fossil fuels to drive the economy. Against this background, Nigeria is considered a good case study for this study.

3. Data and methodology

3.1. Econometric data and methods

Numerous methods have been utilized to investigate the relationship between CO_2 emissions and economic growth (Kumbaroğ;lu et al., 2008). Some strand of studies has employed a single equation model like the Cobb-Douglas production function (Lau et al., 2014; Hamdi et al., 2014) whiles other strands of studies have used other econometric techniques to justify this relationship (Hamit-haggar, 2012; Menyah and Wolde-rufael, 2012). The primary objective of this study is to investigate both the long and short-run relationship between CO_2EFFCO and economic growth. As there are many determinants like economic structure, economic scale and labor/capital ratio for CO_2EFFCO, based on data uniformity, we analyze such a relationship by employing Gross Fixed Capital Formation (GFCF) which is measured as a percentage of Gross Domestic Product (% of GDP), Total labor force (LF), and Trade (TR) (% of GDP) are also used as determining variables in addition to Gross Domestic Product per capita (GDPC) (Dogan and Seker, 2016). LF and GFCF which is based on the Cobb-Douglas production function are selected as determining variables because energy is known to influence productivity (Ameyaw et al., 2017). Thus, the optimization of a production function decides a sequence of optimal savings, investments, and decisions made on consumption. Therefore, labor force and GFCF are likely to influence CO_2EFFCO on a macroeconomic scale if the use of non-renewables surges. TR is also selected as a determining variable because trade is perceived to be the primary causal factor of CO_2EFFCO (Meng et al., 2018). We then take the natural log of all these variables and construct the long-run relationship between the variables above in a linear form, with a view of analyzing the short and long-run and causal nexus among these variables for USA, China, Canada, and Nigeria. All variables except variables in ratio forms have been transformed into natural logarithms (ln) to help mobilize stationarity in the variance-covariance matrix.

$$\ln CO_2EFFCO_t = \beta_0 + \alpha_1 GDPC_t + \alpha_2 GFCF_t + \alpha_3 \ln LF_t + \alpha_4 TR_t + \varepsilon_t \tag{1}$$

where CO_2 represents carbon-dioxide emissions measured in metric ton CO_2EFFCO (Mt CO_2); Gross Domestic Product per capita at Constant 2010 US$ used as a proxy for economic growth; GFCF represents Gross Fixed Capital Formation measured as a percentage of GDP; LF represents the total labor force; TR represents trade measure as % of GDP; β_0 is the constant term; $\alpha_{1...}\alpha_4$ are the coefficients of the model, and ε_t is the error term. Although there are data for GDPC, GFCF, LF, and TR up to the year 2016 with Canada's data ending in 2017, CO_2EFFCO data for all these countries ends in 2016. Therefore, this study leverages annual data throughout 1990–2016 based on data uniformity. The World Development Indicators (WDI) prepared by the World Bank (World Bank, 2015) and the International Energy Agency (IEA) statistics portal is the data source. We present the data for all our variables in Fig. 1 to depict the intricate patterns in our data obtained.

To analyze the short and long-run relationship between CO_2EFFCO and economic growth, stationarity tests are conducted to determine the unit root test of our time series data. This study employs the augmented Dickey-Fuller (ADF), Phillips-Perron (P-P), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests to detect the level of stationarity at $I(0)$, $I(1)$, or $I(d)$ (Dickey et al., 2016; Dickey and Fuller, 2012; Kwon and Shin, 1999; Phillips and Perron, 1988). It is worth noting that if the time series data are not stationary, the regression equation will take the form of spurious regression. Moreover, if the time series data are not stationary at$I(2)$, our computed F-statistics would be invalid because bounds testing hinges on the assumption that variables should be stationary at $I(0)$, $I(1)$,or should take both forms. Based on this background, bound testing is implemented to make sure that none of our variables used in this study is stationary at $I(2)$(Phillips and Perron, 1988).

A surrogate co-integration model introduced by Pesaran et al. (2001) popularly known as the ARDL bounds testing approach is used in this study because of its numerous advantages over the Engle and Granger (1987) and Johansen and Juselius (J-J) (Johanseen and Juselius, 1990) techniques. The Engle and Granger, as well as the Johansen and Juselius techniques, require all regressors in the system to be stationary with an equal order of integration. In testing for co-integration among variables in a small sample, Pesaran et al. leverage more fitting considerations than the J-J and Engle-Granger techniques because these techniques require large data sample for validity (Ghatak and Siddiki, 2001). Second, Pesaran et al. approach can be used whether the underlining regressors are pure of $I(0)$, or of $I(1)$, or mixed while the other co-integration techniques mention herein require that all the variables be integrated on the same order (Pesaran et al., 2001). Third, Pesaran et al. ARDL technique allow variables to possess different optimal lags which is impossible for conventional co-integration applications such as the J-J and Engle-Granger techniques (Ozturk and Acaravci, 2011). Based on the ARDL's numerous advantages over the traditional methods, this current study employs the bound test in examining the equilibrium relationships among variables. In reviewing such a relationship, the unrestricted error correction model (UECM) and the ARDL bound testing approach is used. Our mathematical formulation for each variable and country is presented in equation (2). The UECM is used based on the specification of all the long run relationship variables eliminating the restriction about the presence of any variables. Replacing the long-run relationship by its residuals makes our model an Error Correction Model (ECM) because the Error Correction

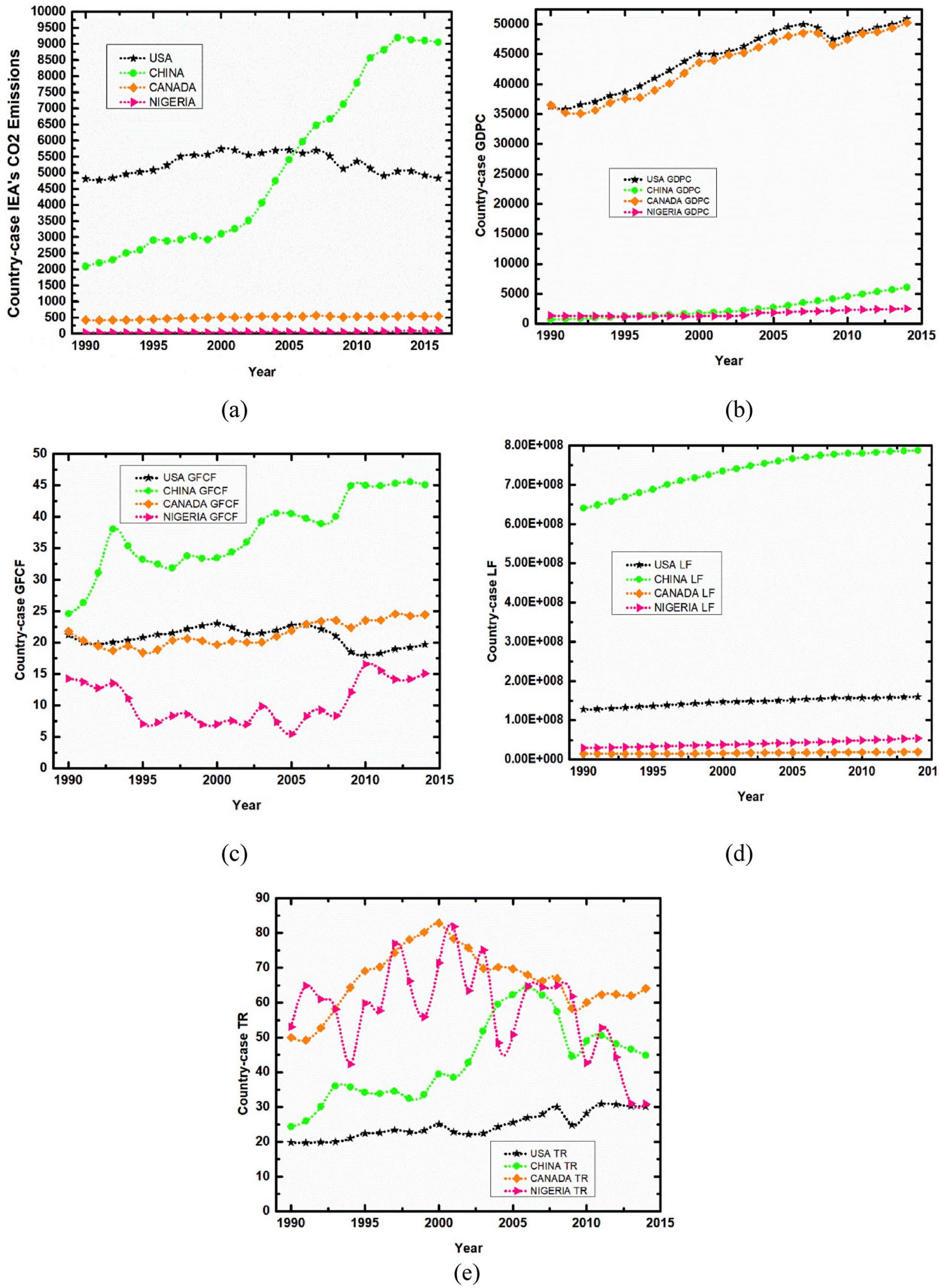

Fig. 1. Country-case data for CO_2EFFCO (**a**), GDPC (**b**), GFCF (**c**), LF (d), TR (e).

Term (ECT) corrects any disequilibrium that can happen in a short period which helps in bringing the situation in a steady state at the long-run.

$$(1-\phi)\begin{bmatrix}\ln CO_2EFFCO\\ GDPC\\ GFCF\\ \ln LF\\ TR\end{bmatrix}_t = \begin{bmatrix}\beta_{01}\\ \beta_{02}\\ \beta_{03}\\ \beta_{04}\\ \beta_{05}\end{bmatrix} + \sum_{i=1}^{j}(1-\phi)\begin{bmatrix}\delta_{11}, \delta_{12}, \delta_{13}, \delta_{14}, \delta_{15}\\ \delta_{21}, \delta_{22}, \delta_{23}, \delta_{24}, \delta_{25}\\ \delta_{31}, \delta_{32}, \delta_{33}, \delta_{34}, \delta_{35}\\ \delta_{41}, \delta_{42}, \delta_{43}, \delta_{44}, \delta_{45}\\ \delta_{51}, \delta_{52}, \delta_{53}, \delta_{54}, \delta_{55}\end{bmatrix} \times \begin{bmatrix}\ln CO_2EFFCO\\ GDPC\\ GFCF\\ \ln LF\\ TR\end{bmatrix}_{t-i} + \begin{bmatrix}\eta_{11}, \eta_{12}, \eta_{13}, \eta_{14}, \eta_{15}\\ \eta_{21}, \eta_{22}, \eta_{23}, \eta_{24}, \eta_{25}\\ \eta_{31}, \eta_{32}, \eta_{33}, \eta_{34}, \eta_{35}\\ \eta_{41}, \eta_{42}, \eta_{43}, \eta_{44}, \eta_{45}\\ \eta_{51}, \eta_{52}, \eta_{53}, \eta_{54}, \eta_{55}\end{bmatrix} \times \begin{bmatrix}\ln CO_2EFFCO\\ GDPC\\ GFCF\\ \ln LF\\ TR\end{bmatrix}_{t-1} + \begin{bmatrix}\varepsilon_1\\ \varepsilon_2\\ \varepsilon_3\\ \varepsilon_4\\ \varepsilon_5\end{bmatrix}_t \tag{2}$$

where $(1-\phi)$ represents the first differencing operator; $\beta_{01}, \ldots, \beta_{05}$ are the constant terms; $\delta_{11}, \ldots, \delta_{55}$ represents the coefficients in the short-run; $\eta_{11}, \ldots, \eta_{55}$ represents the long-run coefficients. To test the existence of a short-run relationship between the variables in (2), we formulate our null and alternative hypothesis as:

H_0: There is no short-run relationship between the variables; thus, $\delta_{ij} = 0$.

H_1: There is a short-run relationship between the variables, therefore, $\delta_{ij} \neq 0$.

Likewise, for examining the possible existence of a long-run relationship, we formulate our null and alternative hypothesis as:

H_0: There is no long-run relationship between the variables; thus, $\eta_{ij} = 0$.

H_1: There is a long-run relationship between the variables; therefore, $\eta_{ij} \neq 0$.

For accepting and rejecting decisions, the following procedures are confirmed by Pesaran et al. (2001):

If $F_s >$ upper bound then H_0 should be dismissed for the variables to be co-integrated.

If $F_s <$ lower bound then H_0 should be accepted for the variables to be not co-integrated.

If $F_s \geq$ lower bound and $\leq$ upper bound then the decision becomes inconclusive.Where F_s represents F-statistic.

Finally, equation (3) is formulated to depict the presence of a unidirectional, bidirectional Granger causality or no causality in the short and long-run.

$$\begin{bmatrix}\Delta \ln CO_2EFFCO\\ \Delta GDPC\\ \Delta GFCF\\ \Delta \ln LF\\ \Delta TR\end{bmatrix}_t = \begin{bmatrix}\beta_{01}\\ \beta_{02}\\ \beta_{03}\\ \beta_{04}\\ \beta_{05}\end{bmatrix} + \begin{bmatrix}\lambda_{11,1}, \lambda_{12,1}, \lambda_{13,1}, \lambda_{14,1}, \lambda_{15,1}\\ \lambda_{21,1}, \lambda_{22,1}, \lambda_{23,1}, \lambda_{24,1}, \lambda_{25,1}\\ \lambda_{31,1}, \lambda_{32,1}, \lambda_{33,1}, \lambda_{34,1}, \lambda_{35,1}\\ \lambda_{41,1}, \lambda_{42,1}, \lambda_{43,1}, \lambda_{44,1}, \lambda_{45,1}\\ \lambda_{51,1}, \lambda_{52,1}, \lambda_{53,1}, \lambda_{54,1}, \lambda_{55,1}\end{bmatrix}\begin{bmatrix}\Delta \ln CO_2EFFCO\\ \Delta GDPC\\ \Delta GFCF\\ \Delta \ln LF\\ \Delta TR\end{bmatrix}_{t-1} + \begin{bmatrix}\lambda_{11,m}, \lambda_{12,m}, \lambda_{13,m}, \lambda_{14,m}, \lambda_{15,m}\\ \lambda_{21,m}, \lambda_{22,m}, \lambda_{23,m}, \lambda_{24,m}, \lambda_{25,m}\\ \lambda_{31,m}, \lambda_{32,m}, \lambda_{33,m}, \lambda_{34,m}, \lambda_{35,m}\\ \lambda_{41,m}, \lambda_{42,m}, \lambda_{43,m}, \lambda_{44,m}, \lambda_{45,m}\\ \lambda_{51,m}, \lambda_{52,m}, \lambda_{53,m}, \lambda_{54,m}, \lambda_{55,m}\end{bmatrix}\begin{bmatrix}\Delta \ln CO_2EFFCO\\ \Delta GDPC\\ \Delta GFCF\\ \Delta \ln LF\\ \Delta TR\end{bmatrix}_{t-m} + \begin{bmatrix}\delta_1\\ \delta_2\\ \delta_3\\ \delta_4\\ \delta_5\end{bmatrix}_t ECT_{t-1} + \begin{bmatrix}\varepsilon_1\\ \varepsilon_2\\ \varepsilon_3\\ \varepsilon_4\\ \varepsilon_5\end{bmatrix}_t \tag{3}$$

where $\beta_{01}, \ldots, \beta_{05}$ represents the constant terms; $\lambda_{11}, \ldots, \lambda_{55}$ represents our variables short-run coefficients; ECT_{t-1} are the error-correction terms of our variables long-run coefficient; $\delta_1, \ldots, \delta_5$ represents the coefficients of the error-correction terms; $\varepsilon_{1t}, \ldots, \varepsilon_{5t}$ are the stochastic error terms. We examine the causal nexus in two approaches. First, we investigate the short-run Granger causalities by the Wald test or F-statistic for the significance of the relevant λ coefficients of the first difference series. Second, the long-run causalities are investigated via the t-test test for the importance of the appropriate δ coefficients on the lagged error correction term. We further assert that if there exists a significant relationship in $I(1)$ variables, then there is a justification of the direction of short-run causality. Also, long-run causality is provided by the t-test of lagged ECT.

3.2. Long short-term memory (LSTM) data source and stepwise algorithm formulation

With the aim of contributing to cleaner energy targets, we focus on forecasting CO_2EFFCO with yearly data for the period covering 1990–2016. Data is obtained from the International Energy Agency (IEA) statistics portal. To test the performance of our LSTM algorithm formulation, we use the period covering 1990–2010 inclusive as training datasets; and 2011–2016 inclusive as testing datasets. Emissions data obtained from IEA measured in metric tons of CO_2 is calculated using IEA's energy balances and the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines. We first present our original data obtained from IEA in Fig. 2.

3.2.1. LSTM sequential algorithm formulation

Here, we focus on improving the robustness of predictions with an LSTM network because LSTM RNNs possess some internal contextual state cells (an input gate, an output gate and a forget gate) called the LSTM cells. Most importantly, the output of the LSTM network will modulate the state of the cells. A system with this property is used because it is essential when the prediction of a neural network tool entirely hinge on the historical content of inputs. Simply put, we employ the LSTM network because it keeps contextual information of data thereby integrating a loop that ensures that information flow from one step to the next. LSTM network has been reported to achieve success and has been implemented in some applications (Abdel-Nasser and Mahmoud, 2017; Zheng et al., 2017). These research from literature leveraged the LSTM network on historical data, and the predictive accuracy of the LSTM output was overwhelming. Our LSTM network algorithm formulation is different from those literature mentioned above. Relative to simulations, LSTM RNNs, require less processing time and report highly accurate forecast outputs and such ideals are crucial to demand and emission forecasting and policies. In our network, an epoch of 300 and a batch size of 12 gave the optimal results. The 12-month batch size is arguably feasible because it is a period good enough to capture the whole emissions data from the previous year. We use cross-validation to check for over-and underfitting.

Our LSTM network consists of three main layers: forget gate layer (f_t), input layer (i_t), and output layer (O_t). The input layer is the original

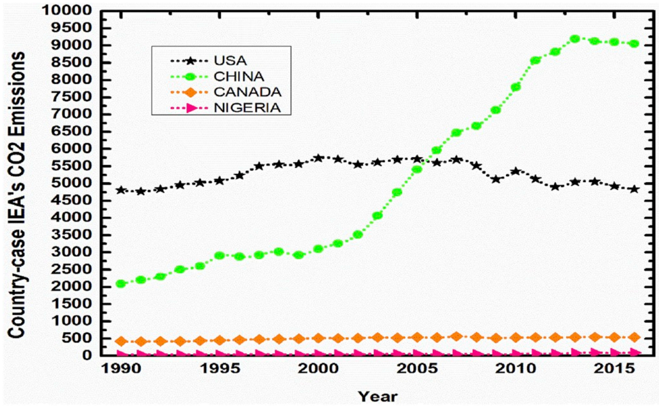

Fig. 2. CO_2EFFCO in Mt CO_2. Emissions are calculated using IEA's energy balances and the 2006 IPCC Guideline.

CO_2EFFCO data, the forget layer concatenates the input layer, and the output layer is the optimal results used in our analysis. The purpose of our forget gate layer is to eliminate previously learned information that is no longer relevant. Our forget layer detects the hidden state from previous time steps and the new input from the current time steps and concatenates them. Our input gate is concatenated and fed into a nonlinear function. Our nonlinear function performs the role as a stopgap for all inputs. The nonlinear function decides to stochastically the values that should be updated at a particular time step based on the current data. The last layer which is the output layer decides which information our network wants to keep when updating all the subsequent cell state. The system also has a sigmoid layer (σ), tanh layer and pointwise operations of summation and multiplication. We formulate our f_t, i_t and O_t as:

$$f_t = \sigma(w_f \times [h_{t-1}, x_t] + b_f) \tag{4}$$

$$i_t = \sigma(w_i \times [h_{t-1}, x_t] + b_i) \tag{5}$$

$$O_t = \sigma(w_0 \times [h_{t-1}, x_t] + b_0) \tag{6}$$

where w_f, w_i and w_0 are the hidden weight in the f_t, i_t and O_t respectively; h_{t-1} represents the unknown vectors at the previous time; x_t is the variable input at a time; and b_f, b_i and b_0 is the biased vector of f_t, i_t and O_t respectively.

The output from the tanh layer (c_t) is formulated as:

$$c_t = \tanh(w_c \times [h_{t-1}, x_t] + b_c) \tag{7}$$

where w_c is the hidden weight from the tanh layer output and b_c is the tanh layer output biased vector.

The output from the current cell state of the cell (C_t) is formulated as:

$$C_t = f_t \times C_{t-1} + i_t \times c_t \tag{8}$$

where C_{t-1} is the cell state of the previous cell. Finally, our hidden vectors (h_t) is expressed as:

$$h_t = O_t \times \tanh(C_t) \tag{9}$$

3.3. Error indexes

As in (Bismark Ameyaw and Yao, 2018a,b), we measure errors from our LSTM network by using the Year-over-Year (YoY) errors, Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Square Error (RMSE). We represent our observed values in a particular year as O_t and F_t as our forecasted values for a specific year. We formulate the YoY errors as:

$$\lambda_t = \frac{|O_t - F_t|}{O_t} \tag{10}$$

where O_t and F_t are the observed and forecast amount of total CO_2EFFCO. Results from (10) are considered undercast if $O_t > F_t$ or of an overcast if $F_t > O_t$. By using MAPE as our benchmark index because our datasets are devoid of extreme values including zero, we formulate our MAD, MAPE, and RMSE error indexes as:

$$MAD = \frac{\sum_{t=1}^{n} \varphi_t}{n} \tag{11}$$

$$MAPE = \left[\frac{100}{n}\left(\sum_{t=1}^{n} \frac{\varphi_t}{O_t}\right)\right] \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (\varphi_t)^2}{n}} \tag{13}$$

where n is the number of the period in a year.

3.4. CO_2 emissions forecasting from fuel combustion and mitigation pathways

For post-2016 CO_2EFFCO projections, data covering the period of 1990–2010 inclusive are used as our training datasets. Emissions projections from 2011 to 2016 inclusive are used as our benchmark test set to make forecasting projections and mitigation pathways from 2017 to 2030 inclusive. In estimating our emission-mitigation pathways, we establish an emission target of negative, zero or one for CO_2EFFCO. We then set an optimal mitigation path as one that registers a high-performance accuracy of at least ninety-eight percent (97%) for our test sets with future emission levels that mimic the decreasing trends and approaches zero or negative.

4. Results and analysis

4.1. Econometric results and analysis

Table 1 shows the results of ADF, P-P, and KPSS tests unit root analysis for USA, China, Canada, and Nigeria. From the table, it can be realized that all variables are stationary after first differencing when the observed values of ADF, P-P, and KPSS test statistics in absolute terms are compared with the critical values of the test statistics at 1%, 5%, and 10% significance levels. The results present substantial evidence of stationarity in both level and first differencing. Against this backdrop, we accept the null hypothesis and conclude that there is unit root in the variables various levels except for some variables like GDPC in the USA, TR in USA and Canada, and CO_2EFFCO in China. Thus, we reject the null hypothesis of non-stationary for the variables in these countries and conclude that those variables are stationary at $I(0)$. Contrary to this, the rest of the variables are stationary $I(1)$.

From Table 2, a long-run equilibrium relationship among CO_2EFFCO, gross domestic product per capita, gross fixed capital formation, labor force, and trade at 1% significance level is found for USA, China, Canada, and Nigeria.

The short and long-run coefficients of all the variables in the countries employed herein are presented in Table 3. In Table 3, it is evident that there exist a significant relationship between CO_2EFFCO and gross domestic product per capita, labor force and trade in USA and China and Canada. However, in the case of Nigeria, there exist a significant relationship between CO_2EFFCO and gross domestic product per capita which reflects the importance and impact of gross domestic

Table 1
Unit root test.

Models	USA			CHINA		
	ADF	PPP	KPSS	ADF	PPP	KPSS
$\ln CO_2EFFCO$	−2.29	−2.26	0.15	−2.36*	−2.84*	0.27**
GDPC	−4.29**	−4.13**	0.21	−1.42	−1.07	0.47**
GFCF	−0.63	−0.03	0.57**	−0.64	−1.09	0.37**
lnLF	−2.73	−2.61*	0.73**	−1.08	−1.12	0.59**
TR	−3.14**	−3.14**	0.64***	−1.96	−1.78	0.43**
$\Delta \ln CO_2EFFCO$	−6.03***	−6.05***	0.11	−6.27***	−9.76***	0.02
ΔGDPC	−3.41**	−3.47**	0.39*	−3.52**	−3.47**	0.13
ΔGFCF	−5.57***	−8.72***	0.01	−4.95***	−4.99***	0.56**
ΔlnLF	−4.79***	−5.33***	0.25	−4.04***	−4.32***	0.07
ΔTR	−4.75***	−4.74***	0.10	−5.01***	−5.06***	0.15
	CANADA			**NIGERIA**		
$\ln CO_2EFFCO$	−1.49	−1.73	0.23	−2.14	−2.03	0.26
GDPC	0.61	0.08	0.47**	−0.97	−1.03	0.54**
GFCF	−1.32	−1.63	0.41*	−2.53	−2.64	0.34
lnLF	−3.21**	−3.24**	0.24	−0.78	−0.87	0.59**
TR	−3.61**	−3.62**	0.78***	1.29	1.18	0.53**
$\Delta \ln CO_2EFFCO$-4.19***	−4.11***	0.14	−6.82***	−7.07***	0.19	
ΔGDPC	−4.07***	−4.10***	0.02	−4.62***	−4.73***	0.11
ΔGFCF	−5.31***	−5.37***	0.14	−7.58***	−9.12***	0.38*
ΔlnLF	−5.43***	−5.41***	0.25	−476***	−4.65***	0.11
ΔTR	−5.21***	−5.09***	0.29	−4.92***	−4.83***	0.18

Notes: (1) ***, **, * represents 1%, 5%, and 10% significance level respectively; (2) For ADF and P-P tests, H_0 = series has a unit root, while for KPSS test H_0 = series is stationary; (3) Critical values for ADF test are: −3.67 (1%), −2.85 (5%), and −2.41 (10%); (4) Critical values for P-P test are: −3.61 (1%), −2.79 (5%), and −2.39 (10%); (5) Critical values for KPSS test are: 0.72 (1%), 0.47 (5%), and 0.34 (10%).

Table 2
F-bound testing with intercept co-integration results.

Models	USA		CHINA	
	F-statistic	Decision	F-statistic	Decision
$F_{\ln CO_2\,EFFCO}(\ln CO_2EFFCO/GDPC, GFCF, \ln LF, TR)$	4.67***	Co-integration	4.19***	Co-integration
$F_{GDPC}(GDPC/\ln CO_2EFFCO, GFCF, \ln LF, TR)$	4.35***	Co-integration	11.07***	Co-integration
$F_{GFCF}(GFCF/\ln CO_2EFFCO, GDPC, \ln LF, TR)$	5.46***	Co-integration	1.91	No co-integration
$F_{\ln LF}(\ln LF/\ln CO_2EFFCO, GDPC, GFCF, TR)$	0.84	No co-integration	1.21	No co-integration
$F_{TR}(TR/\ln CO_2EFFCO, GDPC, GFCF, \ln LF)$	8.27***	Co-integration	5.75***	Co-integration
	CANADA		**NIGERIA**	
$F_{\ln CO_2\,EFFCO}(\ln CO_2EFFCO/GDPC, GFCF, \ln LF, TR)$	12.58***	Co-integration	8.11***	Co-integration
$F_{GDPC}(GDPC/\ln CO_2EFFCO, GFCF, \ln LF, TR)$	1.65	No co-integration	0.92	No co-integration
$F_{GFCF}(GFCF/\ln CO_2EFFCO, GDPC, \ln LF, TR)$	8.26***	Co-integration	1.87	No co-integration
$F_{\ln LF}(\ln LF/\ln CO_2EFFCO, GDPC, GFCF, TR)$	2.17	No co-integration	9.82***	Co-integration
$F_{TR}(TR/\ln CO_2EFFCO, GDPC, GFCF, \ln LF)$	4.45***	Co-integration	6.72***	Co-integration

Notes: (1) *** denotes 1% significance level; (2) F-bound 1% testing critical values used with intercept without any trend are: 4.17–5.98.

product per capita on CO_2EFFCO to the Nigerian economy. Furthermore, the error correction terms (ECTs) in Table 3 are all negative and significant at 1% except for Nigeria. Thus, the negative values of ECTs indicate that any deviation from the short-run disequilibrium among the variables is corrected in each period to return to the long-run equilibrium level. It can also be concluded that the rate of adjustment in returning to equilibrium for Canada is much faster than the USA and China in absolute value. Also, the diagnostic tests in our analysis depict that error terms for short-run models are normally distributed excluding China. The results are free from serial correlation, heteroscedasticity across all the four models.

Table 4 shows the results of our multivariate Vector Error Correction Model (VECM) Granger causality analysis. Unidirectional causality running from gross domestic product per capita to CO_2EFFCO; total labor force to CO_2EFFCO; trade to CO_2EFFCO; and trade to gross domestic product per capita is found for the USA. In China, unidirectional causality running from gross domestic product per capita to CO_2EFFCO; trade to CO_2EFFCO and trade to gross domestic product per capita is

Table 3
ARDL results.

Regressors	USA	CHINA	CANADA	NIGERIA
Short-run coefficients				
ΔGDPC	−0.42***	−0.38***	−0.31***	−0.44*
ΔGFCF	−0.13	0.07	0.16	−0.07
ΔlnLF	−0.23***	−0.44***	−0.21***	0.21
ΔTR	0.49**	0.83***	0.24**	0.09
Constant	0.87	2.39	4.18	−1.86
ECT_{t-1}	−0.45***	−0.43***	−0.51***	−0.18
Long-run coefficients				
GDPC	−0.03	−0.12	−0.41	−0.28
GFCF	0.04	−0.07	0.68	0.73
lnLF	0.14	0.49	−0.75	−0.23
TR	0.27	0.35	−0.39	0.21
Constant	2.16	3.24	0.93	−0.18
R^2-adjusted	0.78	0.92	0.69	0.55
Serial correlation χ^2 (1)	1.83 [0.14]	2.16 [0.09]	0.87 [0.39]	1.12 [0.28]
Hetroscedasticity χ^2 (1)	0.81 [0.31]	0.61 [0.42]	0.59 [0.44]	0.26 [0.57]
Normality χ^2 (1)	2.17 [0.27]	19.23 [0.00]	1.67 [0.48]	0.39 [0.84]
RSS	37.23	19.84	23.91	21.27

Notes: (1) ***, **, * represents 1%, 5%, and 10% significant level respectively; (2) RSS = residual sum of square.

found. For Canada, evidence of unidirectional causality running from gross domestic product per capita to CO_2EFFCO; and from trade to gross domestic product per capita is found. In the case of Nigeria, a unidirectional causality running from trade to gross domestic product per capita is also observed. Finally, we summarize all the results obtained in this study in Table 5.

Table 5
Summary of results.

Causality	**(Economic growth↔CO_2EFFCO)**		
USA	Unidirectional causality (economic growth → CO_2EFFCO)		
CHINA	Unidirectional causality (economic growth → CO_2EFFCO)		
CANADA	Unidirectional causality (economic growth → CO_2EFFCO)		
NIGERIA	No causality direction		
Forecast	**CO_2EFFCO Results**		
	2020	2025	2030
USA	~3087.43MtCO_2	~2121.89MtCO_2	~877.46MtCO_2
CHINA	~7145.23MtCO_2	~5176.77MtCO_2	~3199.21MtCO_2
CANADA	~499.23MtCO_2	~419.36MtCO_2	~321.34MtCO_2
NIGERIA	~83.77MtCO_2	~78.92MtCO_2	~77.72MtCO_2
Pathways	**CO_2EFFCO Results**		
	2020	2025	2030
USA	~3391.41MtCO_2	~1716.18MtCO_2	zero emission
CHINA	~6428.57MtCO_2	~3415.71MtCO_2	zero emission
CANADA	~391.13MtCO_2	~205.63MtCO_2	zero emission
NIGERIA	~60.23MtCO_2	~20.98MtCO_2	zero emission

Table 4
VECM Granger causality test result.

Variables	Short-run					Long-run ECT_{t-1}
	$\ln CO_2EFFCO_{t-1}$	$GDPC_{t-1}$	$GFCF_{t-1}$	$\ln LF_{t-1}$	TR_{t-1}	
USA						
$\Delta \ln CO_2EFFCO$	–	0.11	0.19	0.23	0.14	−0.28***
$\Delta GDPC_t$	4.12**	–	0.06	0.08	0.11	−0.41***
$\Delta GFCF_t$	1.23	0.14	–	0.17	0.21	−0.25***
$\Delta \ln LF_t$	4.97**	0.07	0.10	–	0.14	−0.32***
ΔTR_t	5.14**	4.92**	1.01	1.34	–	−0.27***
	CAUSALITY DIRECTION					
	$GDPC \rightarrow \ln CO_2EFFCO$					
	$\ln LF \rightarrow \ln CO_2EFFCO$					
	$TR \rightarrow \ln CO_2EFFCO$					
	$TR \rightarrow GDPC$					
CHINA						
$\Delta \ln CO_2EFFCO$	–	0.17	0.21	0.18	0.26	−0.61***
$\Delta GDPC_t$	11.12*** -		0.13	0.18	0.27	−0.37***
$\Delta GFCF_t$	1.14	0.07	–	1.04	1.01	−0.42***
$\Delta \ln LF_t$	0.13	0.09	0.16	–	0.21	−0.18***
ΔTR_t	4.87**	5.69**	0.18	0.23	–	−0.21***
	CAUSALITY DIRECTION					
	$GDPC \rightarrow \ln CO_2EFFCO$					
	$TR \rightarrow \ln CO_2EFFCO$					
	$TR \rightarrow GDPC$					
CANADA						
$\Delta \ln CO_2EFFCO$	–	0.19	0.14	0.26	0.23	−0.46***
$\Delta GDPC_t$	4.91**	–	0.28	0.17	0.24	−0.38***
$\Delta GFCF_t$	0.07	0.13	–	0.19	0.08	−0.41***
$\Delta \ln LF_t$	0.27	0.21	0.22	–	0.29	−0.37***
ΔTR_t	0.14	9.14***	0.31	0.21	–	−0.44***
	CAUSALITY DIRECTION					
	$GDPC \rightarrow \ln CO_2EFFCO$					
	$TR \rightarrow GDPC$					
NIGERIA						
$\Delta \ln CO_2EFFCO$	–	0.61	1.23	1.37	1.58	−0.47***
$\Delta GDPC_t$	2.10	–	1.93	1.97	2.13	−0.07
$\Delta GFCF_t$	2.21	2.64	–	2.52	2.87	−0.04
$\Delta \ln LF_t$	0.08	0.17	0.22	–	0.11	−0.06
ΔTR_t	0.07	4.40**	0.18	0.29	–	−0.02
	CAUSALITY DIRECTION					
	$TR \rightarrow GDPC$					

Notes: ***, ** denotes significant level of 1%, and 5% respectively.

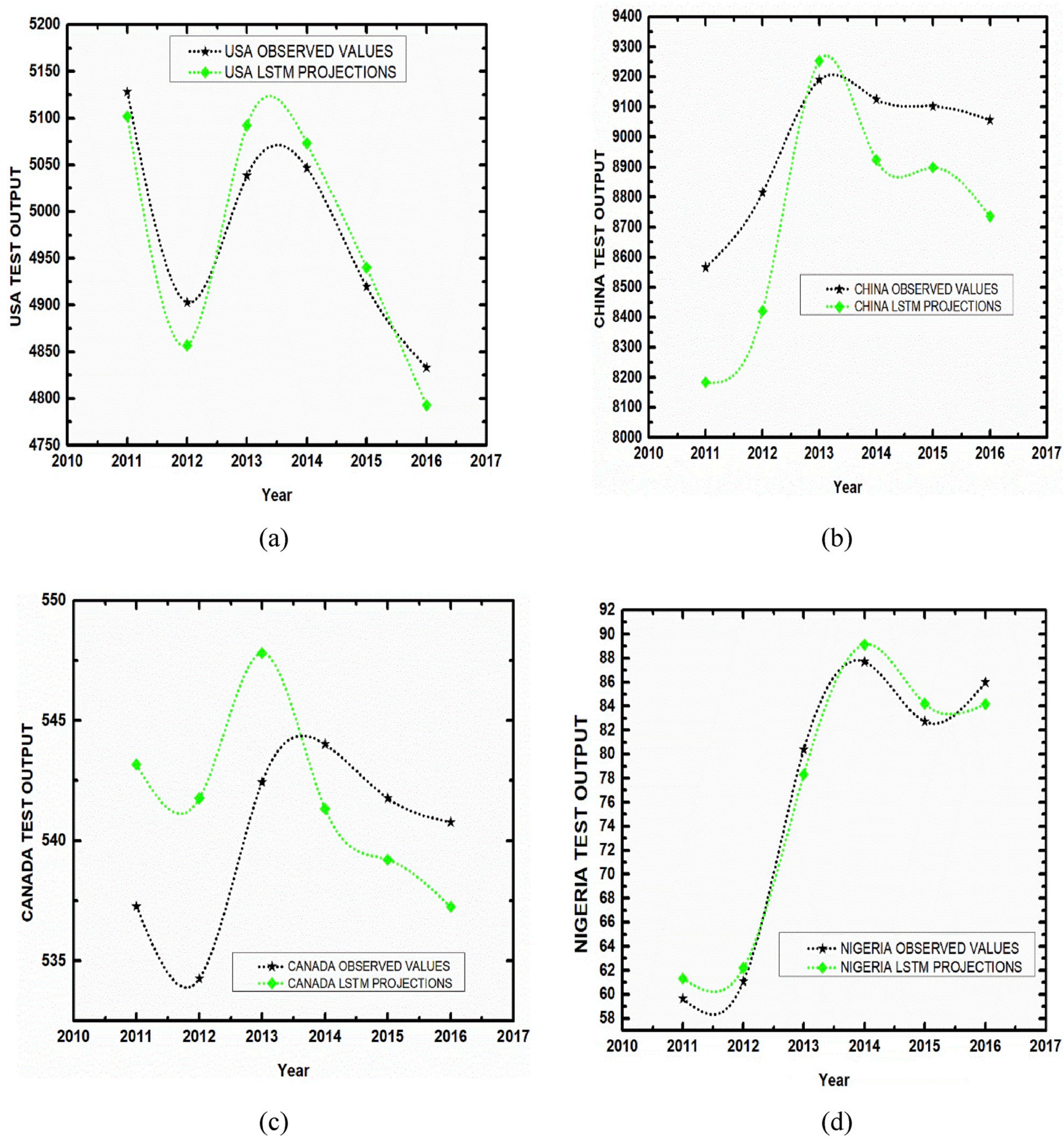

Fig. 3. LSTM network test output performance against observed values for the period covering 2011–2016.

4.2. LSTM testing stage analysis

Here data obtained from IEA for total CO_2EFFCO in metric tons of CO_2 is employed. Checking for the predictive accuracy of our LSTM network, LSTM projections covering the period of 2011–2016 inclusive for the USA, China, Canada, and Nigeria is presented in Fig. 3, while the mathematically formulated values for our error indexes are presented in Fig. 4. From Fig. 3, LSTM network testing stage output performed well against the observed values for the USA, China, Canada, and Nigeria (see Fig. 3a–d). LSTM network test output YoY errors for USA is ~0.51%, ~0.94%, ~1.06%, ~0.53%, ~0.42%, and ~0.83% for the period covering 2011–2016 (inclusive) respectively. MAD of ~35.55 and RMSE of ~37.49 with MAPE accuracy of 99.28% achieved (see Fig. 4). For China, YoY errors of ~4.46%, ~4.45%, ~0.68%, ~2.20%, ~2.23%, and ~3.54% is recorded for the years spanning from 2011 to 2016 (inclusive) respectively. Furthermore, we achieve MAD of ~260.49, RSMSE of ~285.53 with MAPE accuracy of ~97.07% (see Fig. 4). Canada's LSTM network YoY errors are ~1.16% for 2011, ~1.41% for 2012, ~0.99% for 2013, ~0.49% for 2014, ~0.47% for 2015, and ~0.65% for 2016. We record the MAPE accuracy of ~99.15% with a MAD and RMSE value of ~4.59 and ~4.94 respectively (see Fig. 4). Finally, for Nigeria, we achieve YoY errors of ~2.85% for 2011, ~1.85% for 2012, ~2.56% for 2013, ~1.65% for 2014, ~1.79% for 2015, and ~2.12% for 2016. We achieve MAPE

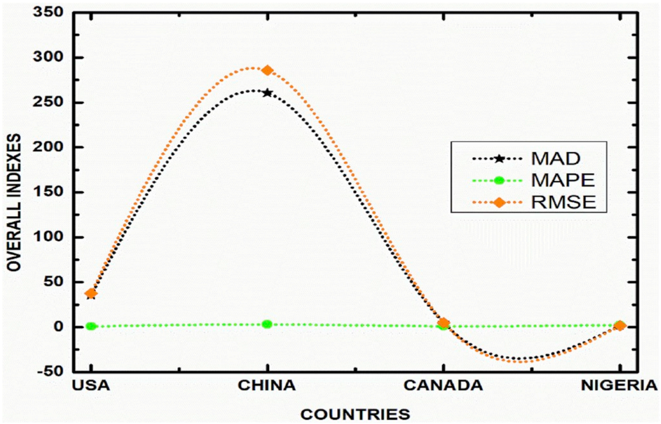

Fig. 4. Error indexes of LSTM network test output performance against observed values.

accuracy of ~97.86% with a MAD and RMSE of ~1.61 and ~1.63 respectively (see Fig. 4). Therefore, the initial assertion of setting a MAPE accuracy of 97% for our emissions-mitigation pathways is achieved for all the countries employed herein.

4.3. CO_2EFFCO forecasting and mitigation pathways

4.3.1. CO_2EFFCO forecasting

Based on the performance of our LSTM network which achieved over 97% MAPE accuracy, we forecast CO_2EFFCO from 2017 to 2030 inclusive for all the countries employed herein. For USA, emissions will hit ~3087.43MtCO_2 in 2020, ~2121.89MtCO_2 in 2025, and ~877.46MtCO_2 in 2030 which is ~81.84% reduction on 2016 emission level of 4833.08MtCO_2 (see Fig. 5a). China's emissions will hit ~7145.23MtCO_2 in 2020, ~5176.77MtCO_2 in 2025, and ~3199.21MtCO_2 in 2030 which is ~64.68% reduction on 2016 emission level of ~9056.80MtCO_2 (see Fig. 5b). Canada's emissions will be ~499.23MtCO_2 in 2020, ~419.36MtCO_2 in 2025, and ~321.34MtCO_2 in 2030 which is ~40.58% reduction on 2016 emission level of ~540.77MtCO_2 (see Fig. 5c). Nigeria's emissions will be ~83.77MtCO_2 in 2020, ~78.92MtCO_2 in 2025, and ~77.72MtCO_2 in 2030 which is ~9.62% reduction on 2016 emission level of ~85.99MtCO_2 (see Fig. 5d).

4.3.2. CO_2EFFCO mitigation pathways

Here, we explore CO_2 emission reductions necessary to achieve long-term global climate goals, such as holding warming below 1.5 and 2 °C relative to pre-industrial levels as stated in the Paris Agreement. For our emission mitigation pathways in Fig. 6a–d, emissions projections for the period covering 2011–2016 are used as a test set although National Energy Modelling Systems (NEMS) has proposed that a test set of three-years is justifiable for emission mitigation pathways. To ensure the predictive accuracy and performance of our mitigation pathways, we decided to look back for seven years. CO_2EFFCO data obtained from IEA depicts a decreasing trend. Thus, the decreasing patterns in data coupled with the prerogative of switching to the use of renewables make it imperative to state that emissions from CO_2EFFCO are expected to decline in the post-2016 period. Therefore, using our LSTM network algorithm formulation, we set a lower bound of zero emissions for the year 2030. To achieve zero CO_2EFFCO by 2030, the USA has to decrease CO_2EFFCO emissions from the current 2016 level of ~4833.08MtCO_2 to ~3391.41MtCO_2 and ~1716.18MtCO_2 by 2020 and 2025 respectively (see Fig. 6a). China will have to reduce its CO_2EFFCO in 2030 by decreasing its 2016 emission level of ~9056.80MtCO_2 to ~6428.57MtCO_2 and ~3415.71MtCO_2 by 2020 and 2025 respectively (see Fig. 6b). Canada will have to decrease its 2016 emission level of ~540.77MtCO_2 to ~391.13MtCO_2 and ~205.63MtCO_2 by 2020 and 2025 respectively (see Fig. 6c). Nigeria will also have to reduce its 2016 emission level of ~85.99MtCO_2 to ~60.23MtCO_2 and ~20.98MtCO_2 by 2020 and 2025 respectively (see Fig. 6d).

5. Discussions

The energy market has attracted much attention due to the gradual transition to a low-carbon economy (Ma et al., 2018). As the world hopes not to experience shortages in energy, supplying energy from naturally replenished resources is the solution. Energy from conventional sources is deemed to fuel some economies. Some economies are in a dilemma as to whether or not to completely eradicate energy consumption from traditional sources. Against this backdrop, the study analyzed the nexus between CO_2EFFCO and economic growth to assist Governments in formulating sustainable policies for an emission-free environment. As it is evident that there is no causal link of this kind in literature, this study goes a step further to formulate an LSTM RNN based algorithm network to forecast total CO_2EFFCO. Again, as we are aware of existing RNN models used in predicting total CO_2 emissions (Bismark Ameyaw and Yao, 2018a,b), we have not yet come across an original research work that seeks to forecast CO_2EFFCO for the USA, China, Canada, and Nigeria. Therefore, to fill this gap, our LSTM network algorithm formulation has forecasted CO_2EFFCO and proposed emission-mitigation pathways for these countries to follow to achieve zero emission-free CO_2EFFCO.

The upward and slightly downward trend in China's data as well as the seemingly linear data trends for USA, Canada, and Nigeria (see Fig. 2) exhibit deep concerns on future CO_2EFFCO. Leveraging on the intricate patterns in our CO_2EFFCO dataset as a motivation, forecasting and proposing future emission-mitigation pathways is considered key to drafting effective policies. With substantial evidence on the predictive accuracy of our LSTM algorithm formulation (refer to the testing stage), we show readers the YoY errors of the performance of our LSTM network as against the observed values for each of the countries employed herein (see Fig. 7). Our LSTM network performance is ascribed to the non-assumption driven variables used as well as the networks ability to keep track of the volatilities in the intricate data patterns (refer to the mathematical formulation of our LSTM network).

With the stepwise algorithm formulation in our data and methodology section, we provide researchers with the mathematical formulation underlying our LSTM network for researchers to either replicate or to use as a benchmark in forecasting future emission levels. Gathering existing literature in this subject area will help Governments to propose emission-free policies by laying out strategic policy scenarios to reduce CO_2EFFCO to a considerable level for the ultimate goal of sustainability.

6. Conclusions and policy implications

First, this study examines the relationship among CO_2EFFCO, gross domestic product per capita, gross fixed capital formation, total labor force and trade in the USA, China, Nigeria, and Canada. To test the long-term relationship between the variables, we employed the ARDL bounds testing technique. Although some variables were stationary,

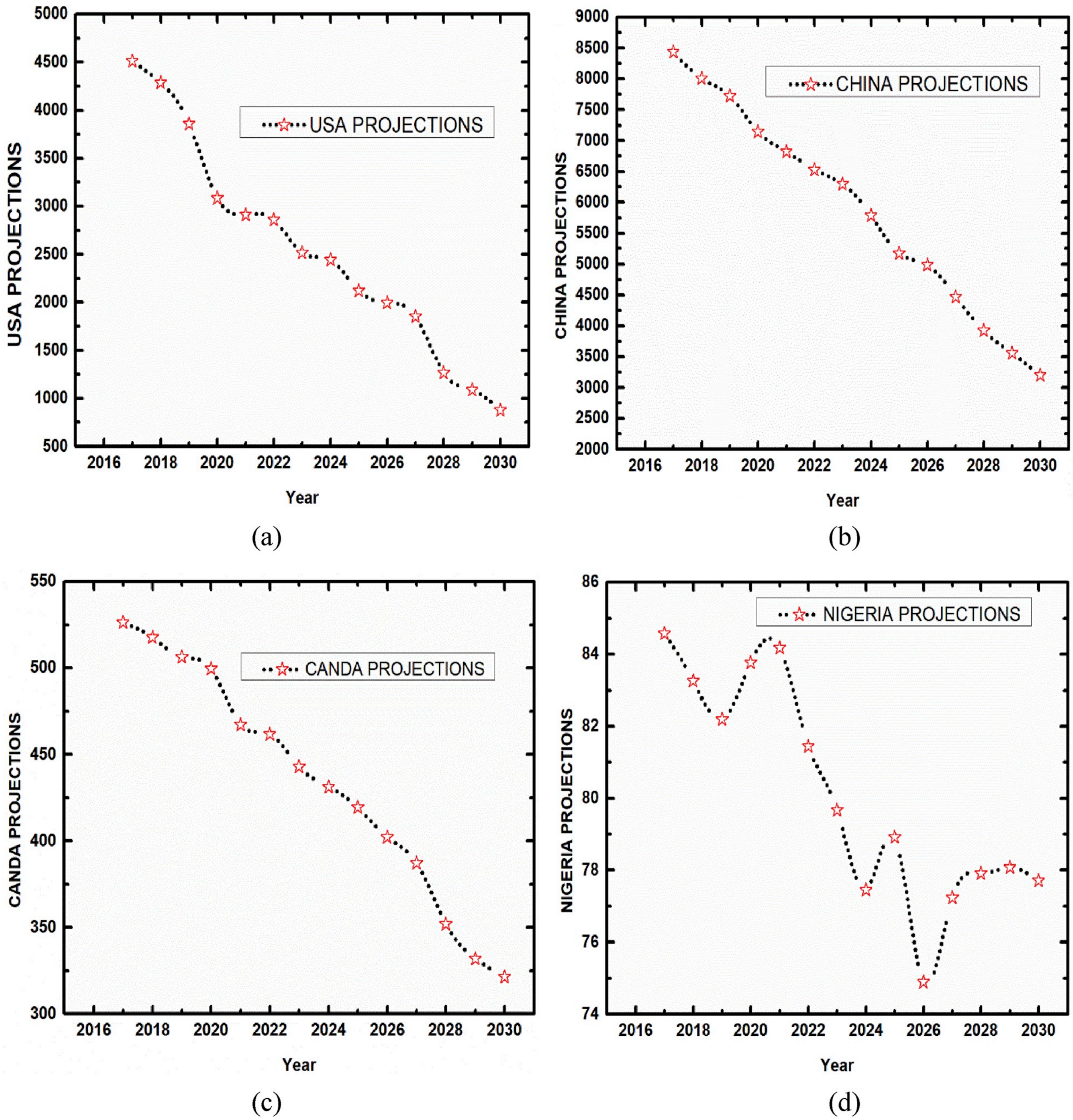

Fig. 5. LSTM network forecast projections for CO_2EFFCO.

$I(0)$, there was enough evidence that all the variables became stationary $I(1)$. Findings from our empirical results showed the existence of a long-term equilibrium relationship among CO_2EFFCO, gross domestic product per capita, gross fixed capital formation, total labor force and trade in all the countries employed herein except Nigeria. Also, as the short-run disequilibrium among the variables is corrected in each period to return to the long-term equilibrium level, we found that the rate of adjustment in returning to equilibrium for Canada is much faster than USA and China in absolute value. Also, in the long-term, evidence of long-run relationship among these variables is found for all countries.

The findings from exploring such a relationship have important policy implications for the USA, China, Canada, and Nigeria not only in terms of environmental perspective but also the efficient allocation of resources for future planning as these countries have recently adopted a more anticipatory approach to addressing environmental issues on the national, and regional levels. Based on the empirical results, if investments in clean energy (Zahonogo, 2017; Abdullahi et al., 2016), cap-and-trade system intensification (S. Zhang et al., 2017b), greater openness to foreign direct investments (Zahonogo, 2017; Abdullahi et al., 2016), and technological innovation in meeting cleaner energy targets (Zahonogo, 2017; Abdullahi et al., 2016) are not instituted, these countries stand a risk of not meeting their Intended Nationally Determined Contributions (INDCs).

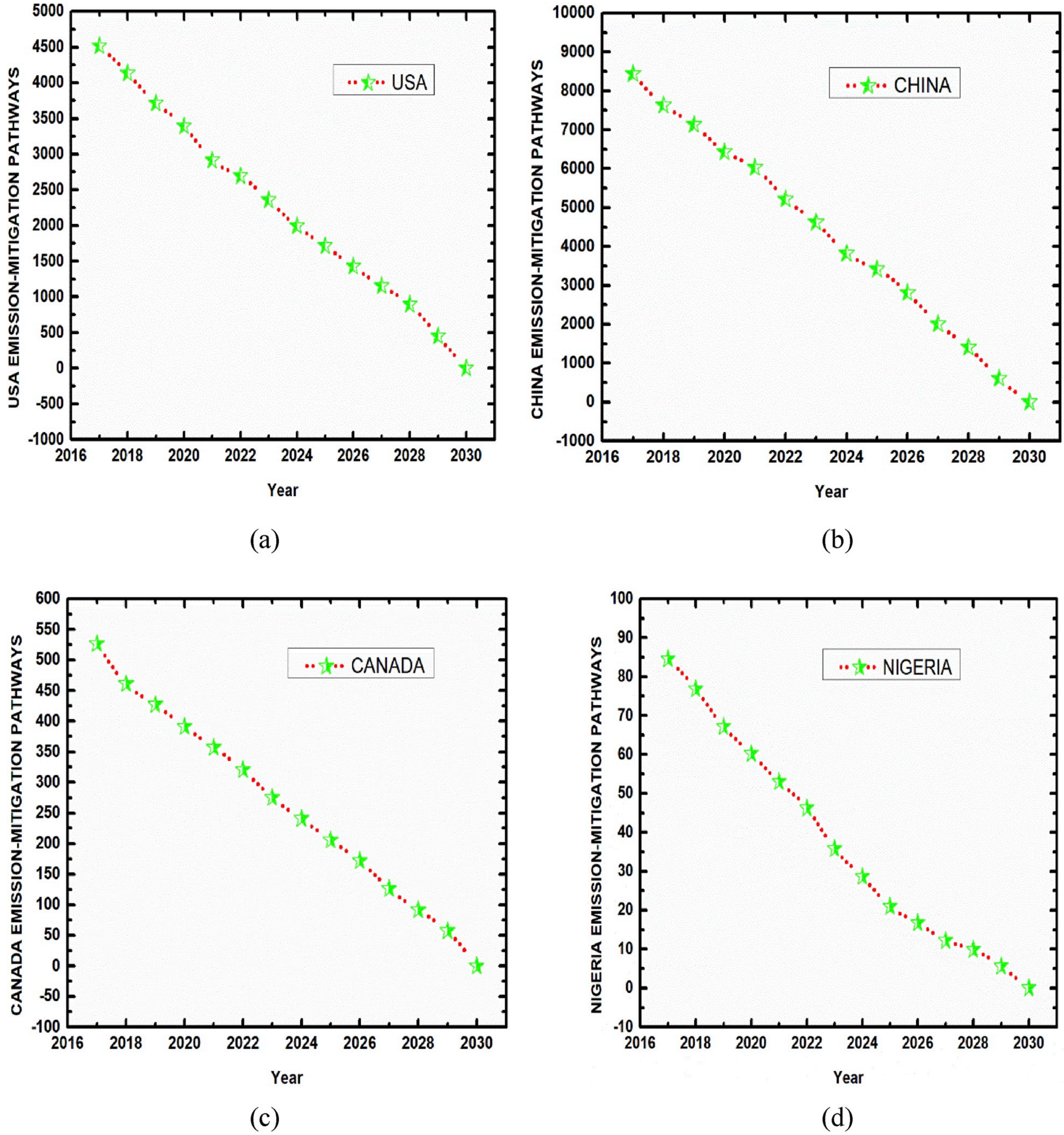

Fig. 6. Emission-mitigation pathways for CO_2EFFCO.

Second, we formulate our algorithm based on LSTM RNN network to forecast and propose emission-mitigation pathways for CO_2EFFCO for the USA, China, Canada, and Nigeria. Our LSTM RNN algorithm formulation outperformed the 97% threshold set for forecasting. We propose emission-mitigation pathways for these countries to follow to achieve zero CO_2EFFCO by the year 2030. Such CO_2EFFCO emission pathways cannot be realized if the USA, China, Canada, and Nigeria fail to adopt mitigation measures like the cap-and-trade system. Also, if mitigation policies do not promote low carbon usage, institute a suitable and functional framework for climate change governance, and encourage investment into energy production from renewable sources, the proposed CO_2EFFCO emission pathways will not be achieved.

7. Future research

Future research in examining the nexus between CO_2EFFCO and economic growth can be investigated in different sectors (such as the agriculture, transport, industry etc.) of the economy for the USA, China, Canada, and Nigeria. Examining the relationship between CO_2EFFCO and economic growth can contribute to the design of energy policies which would form a micro foundation for the aggregate macro-economy. Also, unit root testing with single and two unknown structural breaks can also be applied using any sectoral data. For forecasting and emission-mitigation pathways, rigorous data sets required for any RNN, such as monthly and daily datasets can be utilized to improve the

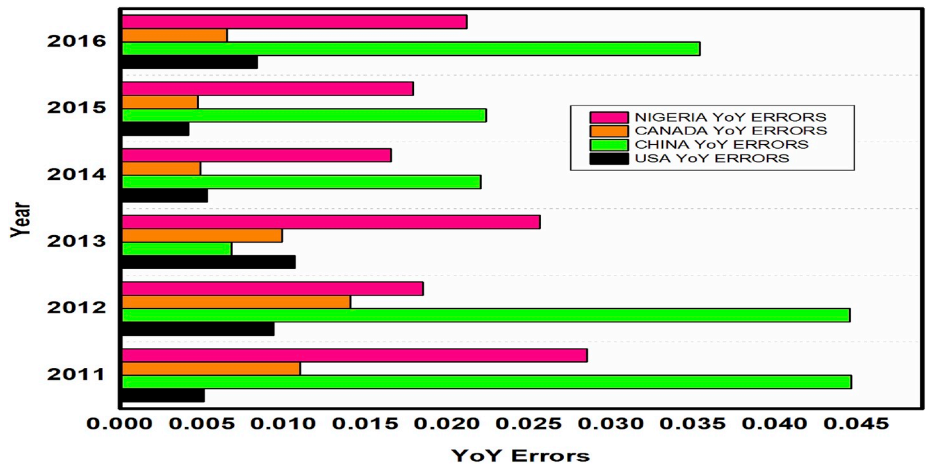

Fig. 7. YoY errors of LSTM network on the observed values.

performance of the LSTM network output against the observed values. On a policy perspective, analyzing the extent to which government structure (centralized and decentralized) affect CO_2EFFCO is worth exploring.

Conflicts of interest

The authors declare no conflict of interest.

Funding

This research is funded by the University of Electronic Science and Technology of China.

Acknowledgments

I would like to thank Professor Li Yao for offering her expert advice throughout the manuscript.

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